Artificial Neural Network Modeling for Improved Coaxial Line-Reflect-Match Calibrations

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Received 11 July 2000; revised 22 August 2000

ABSTRACT: We model a coaxial load using an artificial neural network (ANN) to improve a coaxial line-reflect-match (LRM) calibration of an automatic network analyzer. The ANN is trained with measurement data obtained from a thru-reflect-line (TRL) calibration. The accuracy of the LRM calibration using the ANN-modeled load compares favorably to a benchmark multiline TRL calibration, with an average worst-case scattering-parameter error bound of 0.024 over an 18-GHz bandwidth. Int J RF and Microwave CAE 11: 33–37, 2001.

Keywords: artificial neural network; network analyzer; calibration; model; standards; measurement

I. INTRODUCTION

In this paper, we implement a technique involving artificial neural networks (ANNs) to model the load of a coaxial line-reflect-match (LRM) calibration [1] and improve its accuracy over the equivalent circuit model reported earlier [2]. This approach allows us to develop a compact description of the standard without having to formulate a detailed physical model. ANN descriptions also have a number of advantages over using calibrated measurement data files, as shown in ref. 3. Namely, they are more compact and are less susceptible to noise inherent in measured data, and they can model the standards more accurately at interpolated frequencies, especially for sparse data sets.

The most accurate calibration for coaxial circuits is the multiline thru-reflect-line (TRL) calibration [4], which offers high bandwidth and accuracy through the use of multiple transmission line standards. The calibration also measures the propagation constant of the line standards so that the reference impedance can be set accurately. However, a set of coaxial lines, some relatively long, is required to obtain a wide-band measurement. Coaxial airlines also require considerable care to ensure a good connection without damaging the standard. Furthermore, a set of lines can be costly.

In contrast, the LRM calibration, which requires only a thru connection, a coaxial load, and a reflection, overcomes these limitations. Here, the reference impedance is set to that of a standard load. The impedance of many coaxial loads, however, is nonideal, which can lead to significant error in LRM calibrations.

There are two approaches we can take to characterize an imperfect load. One is to characterize it in terms of its reflection coefficient [5], which requires access to a full multiline TRL calibration set. Alternatively, we can postulate a physical

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model of the load and apply a minimal calibration sufficient to determine the model coefficients [1]. Jargon et al. [2] applied this notion to coaxial lines, employing the measurement of the load after a single-line TRL calibration to fit the parameters of an equivalent circuit model. This provided a means for obtaining an accurate wideband LRM calibration with a compact coaxial standard set consisting of a reflection, a match standard, and a line of short length.

Although the equivalent circuit model used in ref. 2 was effective, there were a number of difficulties with it. First, the model was specifically tailored for the load used, so considerable time was required to develop an adequate model. The load was approximated by the impedance $R + q\omega^2 + j\omega L$, preceded by a lossless line of characteristic impedance Z_0, length l, and effective permittivity $\varepsilon_{r,\mathrm{eff}}$. The value of R was determined by measuring the direct current resistance of the load. Z_0 was chosen to be 50 Ω, and $\varepsilon_{r,\mathrm{eff}}$ was assumed to be 1. Then, L, q, and l were determined by optimizing the model. Another disadvantage of this model is that it is not guaranteed to work for other loads. A completely different impedance might be required to model other loads correctly.

In an attempt to improve the accuracy of the LRM calibration, we used a single-line TRL calibration to train an ANN model of the load. The following sections describe our implementation of ANNs and assess the accuracy of the LRM calibration using the ANN-modeled load, comparing it to the equivalent circuit model and measured data.

II. ARTIFICIAL NEURAL NETWORKS

The ANN architecture used in this work is a feed-forward, three-layer perceptron structure (MLP3) consisting of an input layer, a hidden layer, and an output layer. The hidden layer allows complex models of input-output relationships. The mapping of these relationships is given by ref. 6

$$\mathbf{Y} = g[\mathbf{W}_2 \cdot g(\mathbf{W}_1 \cdot \mathbf{X})],$$

where $\mathbf{X}$ is the input vector, $\mathbf{Y}$ is the output vector, and $\mathbf{W}_1$ and $\mathbf{W}_2$ are the weight matrices between the input and hidden layers and between the hidden and output layers, respectively. The function $g(u)$ is a nonlinear sigmoidal activation function given by

$$g(u) = \frac{1}{1 + \exp(-u)},$$

where u is the input to a hidden neuron. An MLP3 with one hidden sigmoidal layer is able to model almost any physical function accurately provided that a sufficient number of hidden neurons are available [7].

ANNs learn relationships among sets of input-output data which are characteristic of the device or system under consideration. After the input vectors are presented to the input neurons and output vectors are computed, the ANN outputs are compared to the desired outputs and errors are calculated. Error derivatives are then calculated and summed for each weight until all of the training sets have been presented to the network. The error derivatives are used to update the weights for the neurons, and training continues until the errors reach prescribed values.

Although multiple inputs and outputs are possible with this ANN architecture, we made use of one input (frequency) and two outputs (the real and imaginary components) for each measured impedance parameter. In this study, we utilized software developed by Zhang et al. [8] to construct our ANN models.

III. LOAD MODELING

We used a set of commercially available GPC-7 artifacts for these experiments. The artifacts consisted of 2.25-, 10-, and 30-cm airlines, a short circuit, and a nominally 50 Ω coaxial load. We assumed that our sexless GPC-7 connectors mated perfectly with our line, allowing a direct connection between the two ports to serve as a thru line.

In Figure 1 we plot measurements of the real and imaginary parts of the load impedance. The impedance was determined by a TRL calibration using only the thru connection and the 2.25-cm line, and applying an impedance transformation to the calibration, which yielded the measured S-parameters referenced to 50 Ω. The characteristic impedance of the line was determined from its capacitance and propagation constants, allowing the reference impedance of the TRL calibration to be accurately set to 50 Ω [9]. Use of only a

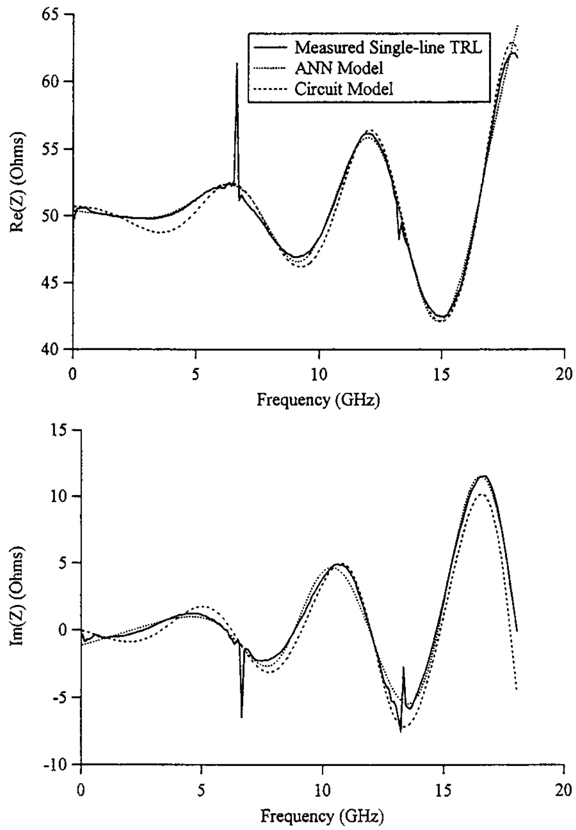

Figure 1. Real and imaginary parts of the measured and modeled impedance of the load.

single line explains the inaccuracy at multiples of 6.67 GHz. The figures show that the load deviates significantly from 50 Ω.

To account for the nonidealities, we developed an ANN model for the load using 15 hidden neurons and 181 measured points. We trained our ANN model with data taken from the single-line TRL calibration to illustrate that loads, or for that matter almost any artifact, can be modeled using only a simple set of calibration standards rather than a large set of expensive airlines. Figure 1 shows that the real and imaginary parts of the ANN-modeled load correspond closely to the measured values and that the model did avoid the spikes present at multiples of 6.67 GHz. Also plotted in Figure 1 are the real and imaginary parts of the load as determined by the equivalent circuit model of ref. 2. Not only does the ANN model match the measured values closer than the circuit model, but it was also developed in a small fraction of the time needed to develop and optimize the circuit model.

IV. CALIBRATION COMPARISON

First, two consecutive multiline TRL calibrations, using all three airlines, were compared to assess the limitations on calibration repeatability caused by contact error and instrument drift. The technique of ref. 10 was used to determine an upper bound on this repeatability error. Briefly, the comparison determines the upper bound for $|S'_{ij} - S_{ij}|$ for measurements on any passive device, where S'_{ij} are the scattering parameters of a device measured with respect to the first calibration and S_{ij} are the scattering parameters measured with respect to the second calibration. The bound is obtained from a linearization, which assumes that the two calibrations are similar to the first order. The result, plotted as a solid curve in Figure 2, roughly indicates the minimum deviation between any pair of calibrations. The average of the worst-case error bounds for repeatability was 0.013.

We also compared the single-line TRL calibration, which was used to develop both the ANN and equivalent-circuit models, to the multiline TRL calibration. The result is plotted in Figure 2. Since we only used the 2.25-cm line standard, our calibration accuracy is poor near multiples of 6.67 GHz, where the difference in line lengths corresponds to a multiple of half a wavelength [4]. Otherwise, the single-line TRL calibration is just as accurate as the multiline TRL calibration at most frequencies.

We assessed the accuracy of the LRM calibrations by comparing them to the 50 Ω multiline TRL calibration. Figure 2 shows the maximum possible difference $|S'_{ij} - S_{ij}|$ where S'_{ij} corresponds to the simple LRM calibration (load assumed to be ideal), and S_{ij} corresponds to the multiline TRL calibration. Here, the difference is large since the reference impedance of the LRM calibration, which is equal to the impedance of the nonideal load, deviates significantly from 50 Ω.

To see how accurate the best LRM calibration was, we compared the multiline TRL calibration to the LRM with a fully characterized load, which involved calibrating the load with the benchmark multiline TRL calibration and using the calibrated measurement data file to define the load. This comparison is once again shown in Figure 2. The average of the worst-case error bounds for this calibration was 0.016.

Figure 2 also shows the worst-case error bounds for the LRM calibrations based on both the ANN

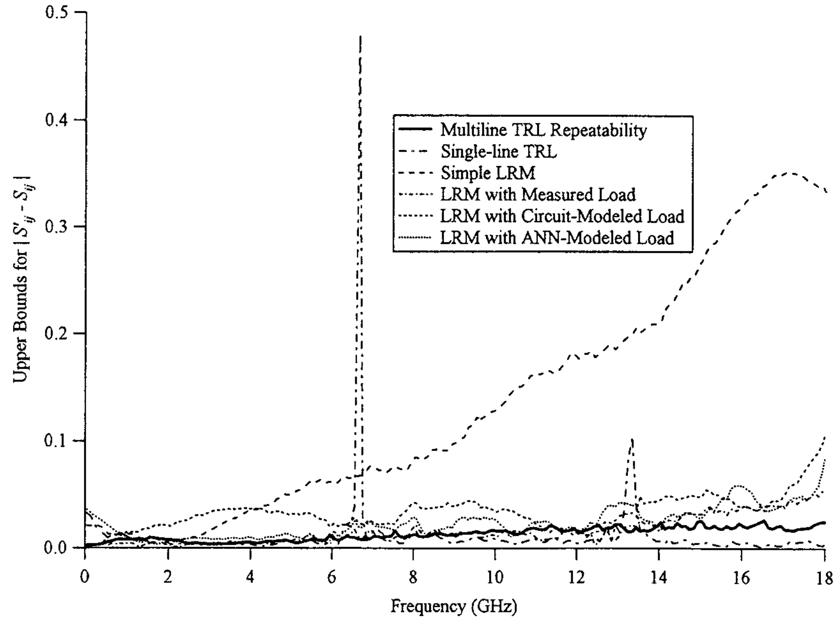

Figure 2. Worst-case error bounds between measurements of passive devices from LRM and TRL calibrations and the multiline TRL calibrations.

and equivalent circuit models. The average of the worst-case error bounds for the ANN-modeled LRM calibration was 0.024, while the average for the circuit-modeled LRM was 0.034.

V. CONCLUSIONS

The use of ANNs to model coaxial LRM load standards compares favorably to a benchmark multiline TRL calibration, with an average worst-case scattering-parameter error bound of 0.024. In our ANN model, we made use of 15 neurons in the hidden layer of an MLP3 architecture.

In the case of LRM calibrations, we have shown that ANN models offer advantages over equivalent circuit models since they do not require detailed physical models. Our ANN model required far less development time than our equivalent circuit model and still managed to achieve higher accuracy. ANN model descriptions are also preferred over calibrated measurement data files since they are much more compact in size. Additionally, loads, or for that matter almost any artifact, can be modeled using only a simple set of calibration standards rather than being fully characterized with a large set of expensive airlines.

REFERENCES

1. D.F. Williams and R.B. Marks, LRM probe-tip calibrations with imperfect resistors and lossy lines, 42nd ARFTG Conf Dig, San Jose, CA, Dec. 1993, pp. 32–36.
2. J.A. Jargon, R.B. Marks, and D.F. Williams, Coaxial LRM calibration, Asia-Pacific Microwave Conf Proc, Taejon, Korea, Oct. 1995, pp. 86–89.
3. J.A. Jargon, K.C. Gupta, and D.C. DeGroot, Artificial neural network modeling for improved on-wafer OSLT calibration standards, Int J RF Microwave CAE 10 (2000), 319–328.
4. R.B. Marks, A multiline method of network analyzer calibration, IEEE Trans Microwave Theory Tech 39 (1991), 1205–1215.
5. D.F. Williams, R.B. Marks, and K.R. Phillips, Translate LRL and LRM calibrations, Microwaves and RF (Feb. 1991), 78–84.
6. P.M. Watson and K.C. Gupta, EM-ANN models for microstrip vias and interconnects in dataset circuits, IEEE Trans Microwave Theory Tech 44 (1996), 2495–2503.
7. F. Wang, V.K. Devabhaktuni, C. Xi, and Q.J. Zhang, Neural network structures and training algorithms for RF and microwave applications, Int J RF Microwave CAE 9 (1999), 216–240.
8. Q.J. Zhang and neural network research team, NeuroModeler, ver. 1.2, Department of Electronics, Carleton University, Ottawa, Canada, 1999.
9. R.B. Marks and D.F. Williams, Characteristic

impedance determination using propagation constant measurement, IEEE Microwave Guided Lett 1 (1991), 141–143.

10. D.F. Williams, R.B. Marks, and A. Davidson, Comparison of on-wafer calibrations, 38th ARFTG Conf Dig, Dec. 1991, pp. 68–81.

BIOGRAPHIES

Jeffrey A. Jargon was born in Denver, CO, in 1967. He received the B.S. and M.S. degrees in electrical engineering from the University of Colorado at Boulder in 1990 and 1996, respectively. He has been with the Radio Frequency Technology Division, National Institute of Standards and Technology (NIST), Boulder, CO, since 1990. His current research interests include calibration techniques for vector network analyzers and artificial neural network modeling of passive and active devices. Mr. Jargon is a member of Tau Beta Pi and Etta Kappa Nu and is a registered professional engineer in Colorado. He is currently pursuing the Ph.D. degree in electrical engineering at the University of Colorado at Boulder.

Kuldip C. Gupta received the B.E. and M.E. degrees in Electrical Communication Engineering from the Indian Institute of Science, Bangalore, India, in 1961 and 1962, respectively, and the Ph.D. degree from the Birla Institute of Technology and Science, Pilani, India, in 1969.

Dr. Gupta has been at the University of Colorado since 1983, initially as a visiting professor and later as a professor. Presently, he is also the Associate Director for the NSF I/UCR Center for Advanced Manufacturing and Packaging of Microwave, Optical and Digital Electronics (CAMPmode) at the University of Colorado. Earlier, he had a long stay (since 1969) at the Indian Institute of Technology, Kanpur, where he was a Professor in Electrical Engineering. On leave from IITK, he has been a visiting professor at the University of Waterloo, Canada; Ecole Polytechnique Federale de Lausanne, Switzerland; Technical University of Denmark (Lyngby); Eidgenossische Technische Hochschule, Zurich; and the University of Kansas, Lawrence. From 1971 to 1979, he was the Coordinator for the Phased Array Radar Group of the Advanced Center for Electronics Systems at the Indian Institute of Technology. On sabbatical from the University of Colorado in 1993–94, Dr. Gupta was a visiting professor at the Indian Institute of Science in Bangalore and a Consultant at the Indian Telephone Industries.

Dr. Gupta's current research interests are in the area of computer-aided design techniques for microwave and millimeter-wave integrated circuits and integrated antennas. He is the author or co-author of six books: *Microwave Integrated Circuits* (Wiley Eastern, 1974; Halsted Press of John Wiley, 1974); *Microstrip Line and Slotlines* (Artech House, 1979; revised second edition, 1996); *Microwaves* (Wiley Eastern, 1979; Halsted Press of John Wiley, 1980; Editorial Limusa Mexico, 1983); *CAD of Microwave Circuits* (Artech House, 1981; Chinese Scientific Press, 1986; Radio I Syvaz, 1987); *Microstrip Antenna Design* (Artech House, 1988); and *Analysis and Design of Planar Microwave Components* (IEEE Press, 1994). Also, he has contributed chapters to the *Handbook of Microstrip Antennas* (Peter Peregrinus, 1989); the *Handbook of Microwave and Optical Components*, vol. 1 (John Wiley, 1989); *Microwave Solid State Circuit Design* (John Wiley, 1988); and to *Numerical Techniques for Microwave and Millimeter Wave Passive Structures* (John Wiley, 1989). Dr. Gupta has published over 170 research papers and holds three patents in the microwave area.

Dr. Gupta is a Fellow of the IEEE (Institute of Electrical and Electronics Engineers, USA); a Fellow of the Institution of Electronics and Telecommunication Engineers (India); a Member of URSI (Commission D, USA); and a Member of the Electromagnetics Academy (MIT, USA). He is a member of the ADCOM for the MTT Society of IEEE, a co-chair of the IEEE MTT-S Technical Committee on CAD (MTT-1), a member of the IEEE Technical Committee on Microwave Field Theory (MTT-15), and on the Technical Program Committees for MTT-S International Symposia. He is the founding editor of the *International Journal of Microwave and Millimeter-Wave Computer-Aided Engineering*, published by John Wiley since 1991. He is on the editorial boards of *IEEE Transactions on Microwave Theory and Techniques*, *Microwave and Optical Technology Letters* (John Wiley), *International Journal of Numerical Modeling* (John Wiley, U.K.) and three journals of IETE (India). He is listed in Who's Who in America, Who's Who in the World, Who's Who in Engineering, and Who's Who in American Education.